DEU FMD 28(82) (2026) 148-156

Dokuz Eylül Üniversitesi Mühendislik Fakültesi Fen ve Mühendislik Dergisi
Dokuz Eylul University Faculty of Engineering Journal of Science and Engineering
Elektronik/Online ISSN: 2547-958X

RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

Design and Production of a Prototype Conveyor Belt for Real-Time Surface Imaging and Data Set Creation

Gerçek Zamanlı Yüzey Görüntüleme ve Veri Seti Oluşturma için Prototip Konveyör Bandının Tasarımı ve Üretimi

Tayyip Özcan [1], Tuğba Baktır [2*], Ahmet Nusret Toprak [1], Ömür Şahin [1], Ömer Enes Yıldız [2], Kübra Yalçın [2], Furkan Korkmaz [3]

[1]Erciyes Üniversitesi Mühendislik Fakültesi Bilgisayar Mühendisliği, Kayseri, TÜRKİYE
[2]Hasçelik Kablo San. Tic. A.Ş, Kayseri, TÜRKİYE
[3]Erciyes Üniversitesi Mühendislik Fakültesi Enerji Sistemleri Mühendisliği, Kayseri, TÜRKİYE
Corresponding Author / Sorumlu Yazar *: tbaktir@hascelik.com.tr

Abstract

In this study, a conveyor belt-based prototype system was developed to create a data set by imaging surface deformations that may occur during the production process of solid aluminum conductors. The system operates using a high-resolution camera integrated into a vision inspection box with controlled lighting and an adjustable viewing angle, capable of capturing images at a resolution of 1280×1024 pixels at a rate of 60 frames per second. The images were collected on the conveyor belt moving at a constant speed, thereby ensuring continuity in image quality. With the developed prototype, a total of 1.600 images were collected and manually labeled as examples of three different defect types. The obtained dataset was organized in a way that will enable the detection and classification of surface defects such as pitting, embossing, and scalping using deep learning algorithms in subsequent stages. In this respect, the study provides the visual data infrastructure necessary for real-time artificial intelligence applications in aluminum conductor production. The prototype was designed using low-cost and easily obtainable hardware and offers a modular system that can be integrated into production lines. The main contribution of this study includes the development of a prototype system that operates under conditions suitable for real production environments. This system is equipped with automated image acquisition capabilities, ensuring consistent and scalable data collection. Additionally, this study provides a new dataset for detecting surface deformations in aluminum conductors. The developed infrastructure aims to form the basis for artificial intelligence-based solutions for industrial quality control systems.

Keywords: *Deep Learning, Conveyor System, Defect Detection, Quality Control, Artificial Intelligence, Machine Design*

Öz

Bu çalışmada, katı alüminyum iletkenlerin üretim süreci sırasında meydana gelebilecek yüzey deformasyonlarının görüntülenerek veri seti oluşturulmasına yönelik, konveyör bant tabanlı bir prototip sistem geliştirilmiştir. Sistem, kontrollü aydınlatma ve ayarlanabilir görüş açısına sahip kapalı bir kutuya entegre edilmiş, saniyede 60 kare hızında 1280x1024 piksel çözünürlükte görüntü alabilen yüksek çözünürlüklü bir kamera kullanılarak çalışmaktadır. Görüntüler, sabit hızda ilerleyen konveyör bandı üzerinde toplanmış ve bu sayede görüntü kalitesinde süreklilik sağlanmıştır. Geliştirilen prototip ile toplamda 1.600 görüntü toplanmış ve bu görüntüler, üç farklı kusur tipine ait olacak şekilde manuel olarak etiketlenmiştir. Elde edilen veri seti, ilerleyen aşamalarda çizik, sıyrık, ezilme gibi yüzey kusurlarının derin öğrenme algoritmaları ile tespit ve sınıflandırılmasına olanak sağlayacak şekilde düzenlenmiştir. Bu yönüyle çalışma, alüminyum iletken üretiminde gerçek zamanlı yapay zeka uygulamaları için gerekli olan görsel veri altyapısını sağlamaktadır. Prototipin tasarımı, düşük maliyetli ve kolay temin edilebilir donanımlar kullanılarak gerçekleştirilmiş olup, üretim hatlarına entegre edilebilir yapıda modüler bir sistem sunmaktadır. Bu çalışmanın temel katkısı, gerçek üretim ortamlarına uygun koşullar altında çalışan bir prototip sistemin geliştirilmesidir. Bu sistem, tutarlı ve ölçeklenebilir veri toplamayı mümkün kılan otomatik görüntü toplama yeteneğine sahiptir. Ayrıca, bu çalışma alüminyum iletkenlerdeki yüzey deformasyonlarını tespit etmek için yeni bir veri kümesi sunar. Geliştirilen altyapı, endüstriyel kalite kontrol sistemleri için yapay zeka tabanlı çözümlerin temelini oluşturmayı hedeflemektedir.

Anahtar Kelimeler: *Derin Öğrenme, Konveyör Sistem, Hata Tespiti, Kalite Kontrol, Yapay Zekâ, Makine Tasarımı*

1. Introduction

Aluminum conductors are widely used in industrial production processes due to their superior properties such as high conductivity, lightness, and corrosion resistance. These conductors are preferred in areas such as electrical energy transmission, the construction sector, the automotive industry, and many other fields. However, various defects may occur on the surfaces of aluminum conductors during the production process. Quality control during the production process is critical to maintaining the mechanical and electrical properties of aluminum conductors, increasing production efficiency, reducing costs, preventing potential defects, ensuring the reliability of the final product, and protecting the company's reputation. Therefore, it is critical to detect defects that may occur on the surfaces of aluminum conductors during the production stage before the products are released to the market [1-3].

DOI: https://doi.org/10.21205/deufmd.2026288219

Geliş Tarihi / Received: 18.04.2025
Kabul Tarihi / Accepted: 09.07.2025

Various surface defects such as pitting, blistering, and flaking occur during the production of aluminum conductors. Such surface defects negatively affect the conductor's mechanical strength and electrical conductivity, reducing product performance and making it difficult to meet specified quality standards. Surface deformations can disrupt material homogeneity and cause critical failures, especially in conductors intended for use under high voltage. Pitting and scaling increase the risk of corrosion by damaging the protective layer on the material's surface. Other defects, such as swelling, result from uncontrollable changes in pressure and temperature during the production process and can threaten the integrity of the material. Early detection of these defects is crucial for improving quality control and reducing costs during the production process.

In the aluminum production process, deformations occur on the surface of conductors for various reasons, and these deformations cause the final product to fail to meet quality requirements. In the current application, these defects are usually detected by visual inspection during the production process [4-6]. However, this traditional method causes problems such as low inspection efficiency, insufficient defect detection rate, and increased labor and costs [7]. With the acceleration of industrialization, traditional methods such as visual inspection have been replaced by non-destructive testing systems based on machine vision, which offer high speed and efficiency [8-11]. In particular, in recent years, the use of image processing-based deep learning methods for detecting defects on product surfaces for quality control purposes has become widespread.

However, the inability to directly apply the systems developed in many studies to production lines highlights the need for prototype lines similar to production lines. These prototype lines play a critical role in processes such as creating data sets for deep learning models, model training, and testing.

In recent years, research in the field of deep learning-based surface defect detection has focused on developing prototype systems for real-time quality control applications on production lines. Zhang and colleagues [12] developed a prototype for defect detection in the quality control of aluminum conductors and adapted this system to the quality control processes of other products. Similarly, Liu et al. [13] collected data for an image processing system to obtain surface images of steels, while Ma et al. [14] designed a visual measurement system for quality control and increased production efficiency of aluminum strips. Çetin Cem et al. [15] designed a prototype capable of real-time defect detection instead of visual inspection for quality control of products purchased from a glass company. Taner et al. [16] presented a prototype machine capable of classifying lettuce seeds by removing foreign matter from the seeds. Li et al. [17] developed a prototype line that operates at a specific speed to collect images of aluminum strips; in another study, a dataset was created using a ball tribometer on a self-propelled disk to detect mechanism wear [18]. Nguyen et al.[19] established a system comprising IR sensors, embedded cameras, and Jetson Nano on an electric cable production line, creating a dataset consisting of a total of 3,879 images and providing PLC-supported automatic quality control. This study emphasizes the importance of collecting data directly from the field and developing integrated systems with deep learning.

Similarly, Shengping Lv et al.[20] published a high-volume, carefully labeled dataset (DsPCBSD+) on printed circuit board (PCB) surface defects (Lv et al., 2024). This dataset, containing 20,276 defects from a total of 10,259 PCB images, has improved model performance thanks to the balanced representation of different defect types. This study highlights the impact of labeling quality on model performance. Güçlü et al. [21] developed both a real-time image acquisition system and a new segmentation-focused deep learning model for detecting steel surface defects. Synthetic data was generated to address class imbalance in the small dataset, significantly improving model accuracy. This approach highlights the importance of synthetic data contributions in prototype systems. Kim et al.[22] established a high-speed imaging system based on a line scan camera for detecting soldering defects on PCB surfaces and supported it with deep learning-based analysis. Acquiring images from different angles in a rotating table system enabled the detection of small and complex defects on the surface, and the system was successfully applied in an SMT factory. In the automotive industry, Ren et al.[23] developed the YOLOv8-WD model to detect defects in the laser welding process and integrated their system into the production line. The dataset of 5,200 examples collected using a high-resolution camera and ring LED lighting enabled the model to perform well even in classes with few examples. This demonstrates the power of model design tailored to the production environment. Finally, Pallavi D. et al.[24] investigated the effect of labeling strategies on model performance for defect detection on metal surfaces using the YOLOv5 model. In particular, an average accuracy increase of 12–25% was observed in datasets with individual and precise labeling compared to group labeling. This study highlights that data quality is at least as critical as model selection.

The complexity of production processes and the existence of uncontrollable variables in field conditions make direct system applications quite difficult. Interruptions in the production line pose significant risks in terms of both time and cost. Therefore, prototype production in the early stages of projects is a more practical and efficient approach than direct field application. Prototype production allows new technologies and methods to be tested in a controlled environment before being used in real-world conditions. This enables potential issues that the system may encounter in the field to be identified in advance, and swift solutions to be developed.

In this study, an original prototype system was designed and developed to prepare a reference data set that will form the basis for future defect detection systems aimed at detecting surface defects in aluminum production lines. In the literature, the lack of high-quality data sets for real-time and reliable detection of aluminum surface defects in industrial production environments stands out as a significant research gap. The developed prototype system is designed to be directly applicable in field conditions, capturing real-time images of the aluminum conductor surface during production and capturing images containing various types of surface defects.

The main contribution of this work is that it provides a realistic prototype system and a reference dataset that will increase the applicability of deep learning-based systems for detecting aluminum surface defects in industrial conditions. The images collected through this prototype provide a high-quality dataset that will be used to train deep learning models. Additionally, this system provides an important resource for future studies that aim to reduce defect rates and increase production efficiency compared to traditional visual inspection methods.

2. Materials and Methods

In this study, a prototype system has been developed for real-time data collection to detect surface defects that may occur during the production process of aluminum conductors. The prototype features a structure that integrates mechanical and electronic systems, providing the necessary hardware and

software infrastructure for recording surface images. The primary objective of the system is to create a surface defect dataset based on image processing techniques. In this regard, the system offers a platform for the immediate analysis of surface defects that may occur during production, thereby laying the groundwork for the development of future quality control systems.

2.1. Prototype Design

In this study, a prototype conveyor belt system has been developed for the application of image processing techniques to detect surface defects in aluminum conductors. The two-dimensional technical drawing of this system, designed under laboratory conditions, is presented in Figure 1.

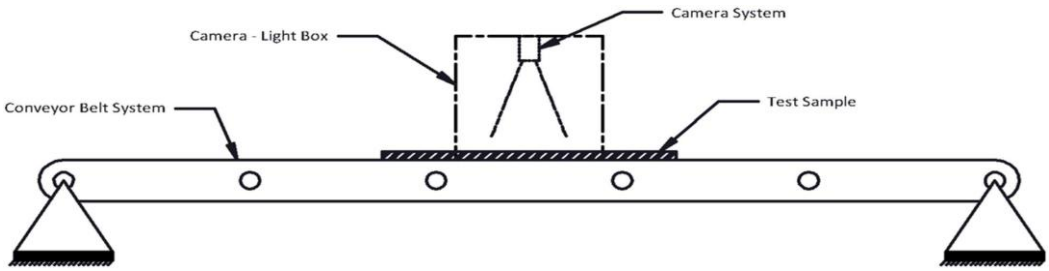


Figure 1.2D Demonstration of an Image Processing Prototype Conveyor System.

The prototype has been optimized to image surface defects with high accuracy and transfer them to a data set. Conductive products moving at a specific speed on the conveyor belt are continuously monitored by high-resolution cameras mounted on the system, and images are captured seamlessly. The design process was planned in detail to include not only the mechanical structure but also the strategic positioning of the imaging and sensing systems. The sensors are positioned to enhance the performance of the image processing algorithms. To prevent the system from being affected by external environmental conditions, all camera and lighting units are housed in a closed box structure that blocks external light ingress. This structure eliminates the negative effects of changes in ambient light on image quality. In addition, the intensity and color of the LED lighting used in the system are adjustable, allowing for lighting conditions suitable for different surface structures. To prevent reflections and glare during imaging, the background surface is designed to be matte and black. This increases the contrast and image clarity required for detecting surface defects.

Similar prototype lines are available in the literature for different applications; however, this study is structured to create the first dataset specific to surface defects in aluminum conductors.

Another notable technical innovation of the system is a special mechanism that allows the camera module to be moved vertically. This eliminates focusing issues that may arise from height differences or positioning problems on the surface, ensuring stable image quality. This feature is rarely found in similar studies and provides a unique contribution to improving the system's imaging accuracy.

The dataset obtained with this system is one of the first examples of high-resolution, classification-ready labeled data sets containing surface defects encountered in the production processes of aluminum conductors. The labeling process was performed manually using LabelMe software, and each defect type was classified in detail. In this regard, the created dataset serves as an important resource for both academic research and industrial applications.

The conveyor line system shown in Figure 1 consists of two main components. The first component is the conveyor belt mechanism that transports the products. The second component is the camera system used to collect data on surface defects. The detailed design of the system was modeled in three dimensions using SolidWorks software, as shown in Figure 2(a). The technical specifications and functions of these two components are discussed in detail below.

The dimensions of the image processing system that collects data on the surface of the products (length: 1910 mm, width: 350 mm, height: 610 mm) are shown in Figure 2(b). These dimensions have been carefully optimized to ensure that the system is positioned optimally on the products and that the surfaces are effectively tracked. The system has been designed to be suitable for testing in a laboratory environment.

(a)

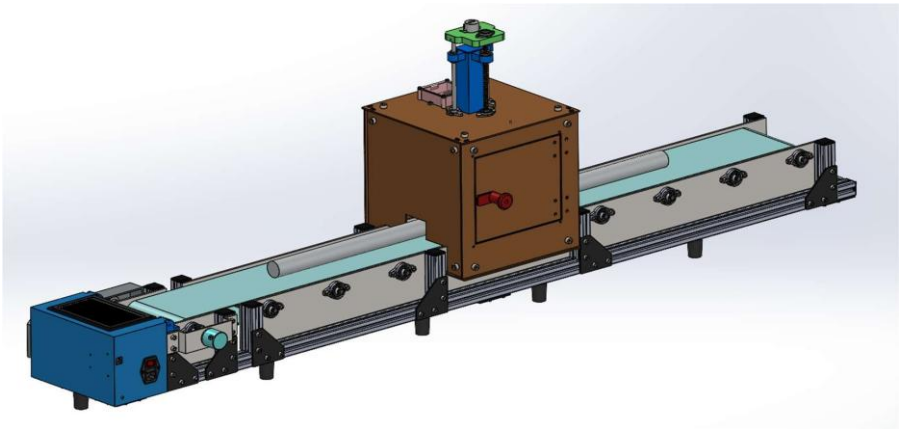


Figure 2. *(Continued)*

(b)

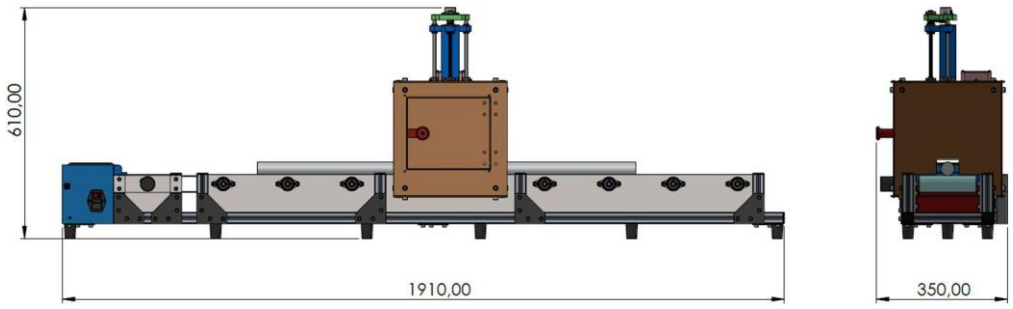


Figure 2. Conveyor belt system: (a) isometric view; (b) front, side, and top views with basic dimensions.

Each step in the diagram clearly shows the assembly sequence of the system components and the relationships between them. First, the sigma profiles that form the basic infrastructure of the system are assembled, and in the subsequent stages, the main structure is completed with the integration of mechanical components such as conveyor drums, roller bearings, and conveyor belts. In the subsequent process, encoders, motors, and camera systems are integrated to ensure the seamless operation of electronic and mechanical systems, followed by the addition of electrical wiring and control elements. The assembly flow diagram of the produced conveyor belt system is detailed in Figure 3.

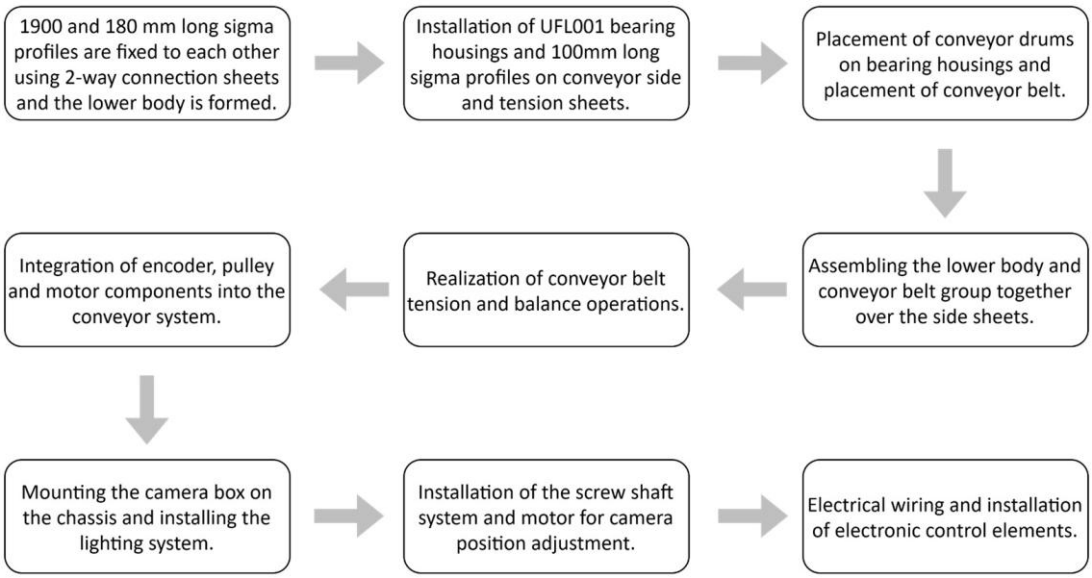


Figure 3. Assembly Flow Chart.

2.2. Electronic circuit design

The general structure of the system includes the integration of motors and drivers, rotary encoders, touch screens, and other peripheral devices with the Arduino Uno microcontroller. The system's power supply is provided by a converter and LM2596 voltage regulators, which are powered by 230V AC and have an output voltage of 24V DC. Operator inputs are received via the Nextion touchscreen, and motor speed data is controlled by the rotary encoder. This integration and control structure is shown in Figure 4.

Arduino Uno was chosen because the system includes multiple units and these units can be controlled from a single microcontroller. The software for the microcontroller was developed in the Arduino IDE environment. In the software, “Nextion” and ‘SoftwareSerial’ libraries were used to communicate with the Nextion screen, while the “RobojaxBTS7960” library was used to control DC motors. Mathematical operations were performed through the ‘math’ library, while the necessary input assignments and variable transformations were defined using the ‘stdio’, ‘stdlib’ and ‘string’ libraries.

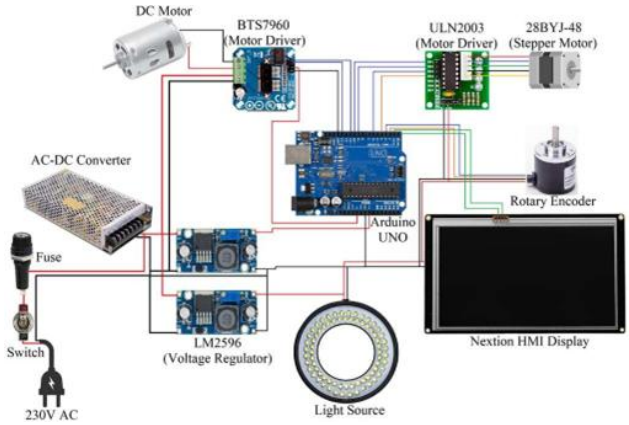


Figure 4. Electronic circuit schematic.

The forward and backward movement of the conveyor line was provided by a 55ZY24-25-02 DC motor and a BTS7960b motor driver. In order to overcome the blurring problems caused by the distance between the camera and the object, which is one of the difficulties encountered in object detection, a 28BYJ-48 model stepper motor and ULN2003 stepper motor driver were used to move the camera on the vertical axis [25]. Within the scope of the software, precise acceleration controls were developed for the stop, start, acceleration, and deceleration functions of the DC motor to prevent sudden movements on the conveyor line. To control the motor speed with high precision, the speed data received from the encoder was compared with the speed value entered by the operator via the Nextion screen.

In terms of peripherals, the information entered by the operator on the Nextion screen was transmitted to the microcontroller via the UART communication protocol. A rotary encoder model OVW6-036-2HC was used to obtain the speed information of the conveyor line. To prevent the acquired data set from being affected by outdoor conditions, artificial lighting was used in an indoor environment [25].

Details to improve the transparency and technical rationale of the prototype design are shown in Table 1. This table lists all the mechanical, electrical, and optical components used in the system. For each component, the purpose of its use and the rationale behind its selection are provided, based on criteria such as material properties, mechanical strength, compatibility, durability, and performance requirements. This organized presentation ensures a systematic understanding of how each component contributes to the overall functionality, reliability, and adaptability of the smart conveyor system.

3. Results

With the completion of the software integration, the final version of the prototype system is presented in Figure 5. The inclusion of the system software increased the functionality of the prototype and enabled real-time data collection, analysis and control processes to be carried out uninterruptedly. At this stage, the mechanical and electronic components of the system worked in harmony with each other and contributed to the creation of an integrated structure.

The features of the prototype conveyor line produced are shared in Table 2.

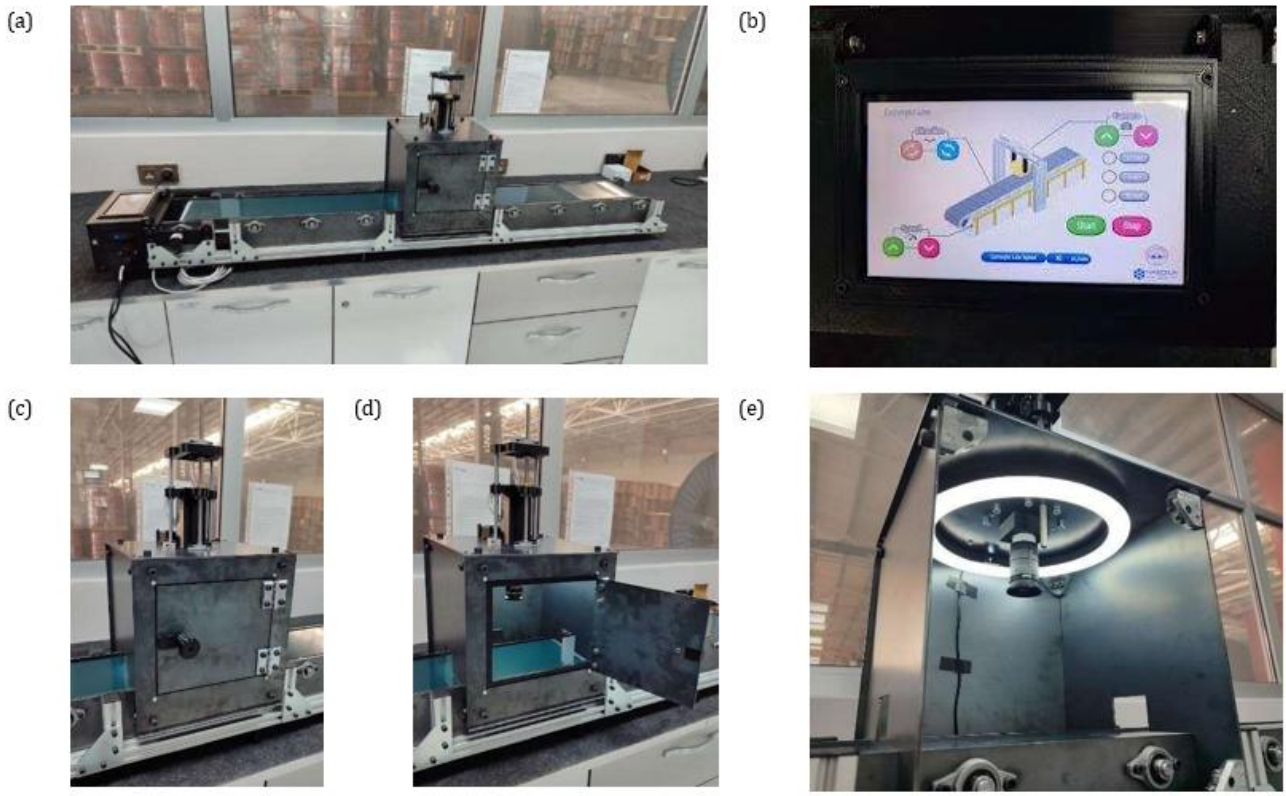


Figure 5. Image Processing Prototype Line Images; (a) View of the Whole Device; (b) Device User Interface; (c) Camera Box; (d) Camera Box Cover Opening, (e) Lighting and Camera System Inside the Camera Box.

Table 1. Materials and components used in the prototype conveyor system, with functional purposes and justifications for selection.

No	Material Name	Purpose of Use	Reason for Selection
1	30x30 Sigma Profile	Used to form the carrier frame structure of the conveyor belt system.	Made of 6063-T5 aluminum; density ~2.7 g/cm³, tensile strength ~190 MPa, includes 8 mm slots for mounting.
2	30x30 Two-Way Bracket	Used to fix sigma profiles at right angles.	Made of 2 mm galvanized steel, provides a 90° connection, compatible with M6 fasteners.
3	40x40 Triangular Corner Bracket	Used to rigidly connect carrier structure elements.	3 mm thick sheet provides high rigidity with up to 500 N·m moment resistance.
4	Sheet Metal	Used to form the body of the conveyor belt system.	1.5 mm ST37 sheet; tensile strength ~370 MPa, easy to bend and form.
5	Conveyor Belt	Used to perform material transport.	3 mm thick, Shore A 65 hardness, friction coefficient μ ≈ 0.6, 10,000-hour lifespan.
6	Plastic Foot	Used to ensure stable contact with the ground.	Adjustable height prevents floor damage.
7	55ZY24-25 24V 300RPM DC Motor	Used for driving the conveyor belt system.	24V, 300 RPM, 1.2 Nm torque output.
8	Arduino UNO	Used to compute motor speed control.	16 MHz clock, 32 KB memory, easy to program.
9	BTS7960 Motor Driver	Used to control motor speed and direction with Arduino.	Supports up to 43 A current, 25 kHz PWM frequency, Arduino compatible.
10	230V Switched Socket	Used to supply power to the system.	Allows safe power control with a switch.
11	GT2 40-Tooth Pulley	Used to transmit rotary motion between the motor and the pulley.	2 mm tooth pitch, compatible with GT2 belts.
12	GT2 Belt	Used to transmit power between pulleys.	2 mm pitch, 6 mm width, low stretch, high precision.
13	KFL001 Bearing Unit	Used to support the conveyor drive pulley.	12 mm inner diameter, 700 N load capacity, works up to 5000 RPM.
14	Drive Pulley	Used to rotate and transport materials via conveyor belt.	Selected for mechanical durability and compatibility with the belt.
15	Rotary Encoder	Used to measure the rotation speed and position of the drum.	600 PPR resolution, 5–24V operation, provides precise feedback.
16	7" Touchscreen	Used to set system parameters and user interaction.	Provides a wide display and user interface.
17	6mm Flexible Coupling	Used to connect the encoder and drum with a misalignment tolerance.	±1° misalignment tolerance, 1.5 N·m torque, vibration damping.
18	KFL08 Bearing Unit	Used to support the lead screw.	8 mm inner diameter, 400 N load capacity, easy mounting.
19	8mm Steel Shaft	Used to support a linear motion mechanism.	HRC 60+ hardness, Ra < 0.2 μm surface roughness, suitable for linear systems.
20	SHF8 Shaft Support	Used to fix the steel shaft.	Fits 8 mm shafts, ±0.05 mm positioning accuracy.
21	LM8UU Linear Bearing	Used for linear motion along the steel shaft.	8 mm inner diameter, low friction, 500 N load capacity.
22	T8 Nut	Used for linear motion with the lead screw.	8 mm diameter, 2 mm pitch, 4-start thread for precise motion.
23	8mm Lead Screw	Used to drive the linear camera mechanism.	T8 standard, 2 mm pitch, high accuracy.
24	28BYJ-48 Stepper Motor	Used to transmit rotary motion from stepper to lead screw.	5V input, 4096 steps/rev, 34 mN·m torque, cost-effective.
25	GT2 20-Tooth Pulley	Used to control stepper motor motion and direction.	2 mm pitch, 20 teeth, compact and precise.
26	ULN2003 Stepper Driver	Used to power the stepper motor.	500 mA output, fully compatible with 28BYJ-48 motor.
27	LM2596 Voltage Regulator	Used for image processing over the conveyor system.	4–40V input, 1.25–37V output, up to 90% efficiency.
28	Basler Camera	Used to provide a suitable optical field for the camera.	Industrial quality, high resolution, software support.
29	Basler Lens	Used to provide uniform illumination in the camera field.	Fully compatible with Basler camera, high optical quality.
30	Ring LED	Used for fixed mechanical support of the lighting unit.	6000K color temp, 24 LEDs, uniform and stable lighting.

Table 2. Prototype line specifications.

Features	Description
Line speed	Ability to operate between 1 and 37 m/min line speed range and precise accuracy with encoder.
Line direction	Ability to work in two directions.
Camera height adjustment	120 mm vertical axis mobility.
Camera motion sensitivity	0.1, 1 and 10 mm precision movement.
Conveyor belt width	150 mm line width.
Conveyor line length	1500 mm line length.
Camera cabinet size	300x300x300 mm camera cabinet size.
Lighting system	Ability to select 3 different colors and adjust brightness (Max. 800 lm)
Supply voltage	230V AC
Control panel	Easy operation with 7" touch screen

This study does not aim to develop a direct error detection system, but rather to design and produce a conveyor belt and imaging system that can be used for similar purposes. Using the completed prototype system, images of various defects on the surfaces of aluminum conductors were collected, thereby creating a new and unique dataset. This dataset, named the Aluminum Conductor Defect Dataset, is suitable for use in deep learning and image processing-based studies on aluminum conductor surface defects.

There are three different types of defects in the dataset: embossing, scalping, and pitting. The number of examples for each of these defects is summarized in Table 3. Embossing defects appear as irregular bumps or marks on the surface and are usually caused by mechanical pressure applied during the production process. Scalping defects are characterized by noticeable peeling, wear, or removal of a layer of the surface in some areas. Pitting, on the other hand, is a defect type that forms as small pits or indentations on the surface and can be caused by corrosion or processing errors.

This dataset can be used for the automatic detection and classification of defects in future deep learning and machine learning-based studies. It is expected to contribute to the development of more advanced and reliable systems for quality control and defect analysis in aluminum conductor production processes.

Table 3. Details of the proposed Aluminum Conductor Defect Dataset.

Defect Type	Number of Images
Pitting	423
Embossing	400
Scalping	801
TOTAL:	1624

The images obtained were labeled using the LabelMe program [26]. The labeled images are presented in Figure 6

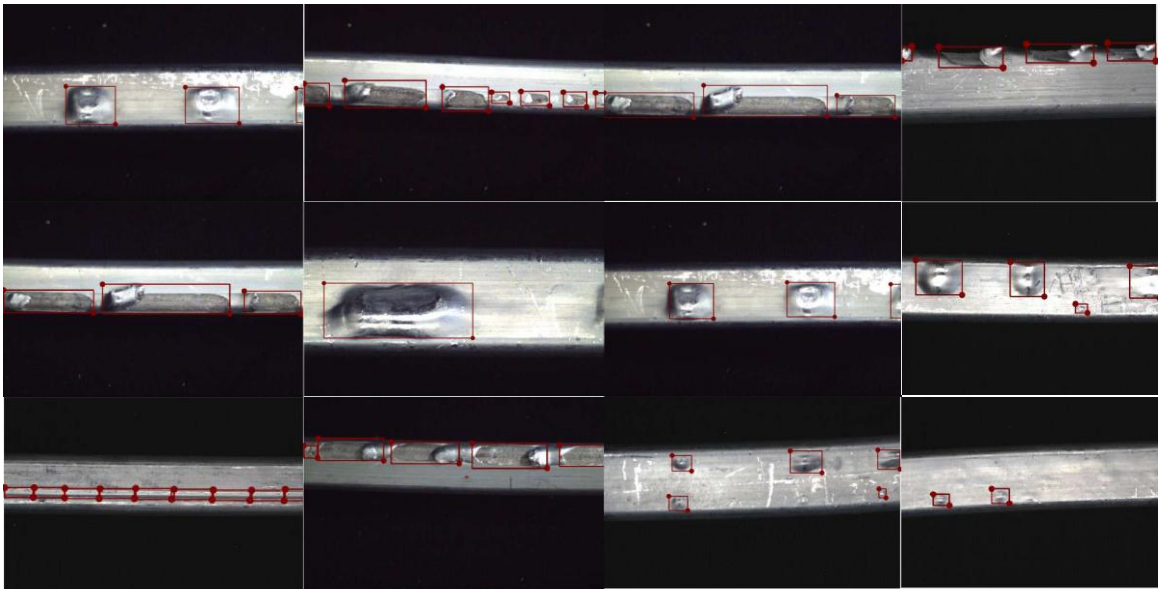


Figure 6. Labeled images obtained with the prototype,

4. Discussion

The Aluminum Conductor Dataset obtained using the conveyor belt and imaging system developed in this study provides a new and original dataset that will contribute to the literature on the detection and classification of aluminum conductor surface defects. The embossing, scalping, and pitting defects present in the dataset created from the images produced by the system are among the common defects encountered in quality control processes in the industry and are consistent with similar defect types reported in the literature [17],[18], [22].

The findings obtained, particularly when evaluated in terms of image quality and the system's ability to distinguish defect types, are comparable to similar systems in the literature (e.g., automatic optical inspection systems and fixed camera-based platforms). For example, when compared to the attention- based lightweight defect detection system developed by M. Wang et al. [18], the system developed in this study was specifically designed for data set production and, thanks to its modular structure, has the potential to be easily integrated into different production lines. The mechanism used in the system's design, which allows the camera position to move vertically, enables it to be adapted not only to a single product type but also to products of different sizes and geometries. This structure allows for quick and precise focus adjustment, making the system easily adaptable to different production scenarios and product varieties. Thus, the system can flexibly collect data sets during production processes and enable high- quality images to be obtained for products with various surface characteristics. However, in order for the system to be used in industrial-scale applications, the imaging speed and automatic labeling capabilities need to be further developed. One of the main limitations encountered in the study is the difficulty of ensuring sufficient image stability in high-speed production lines. Additionally, the imaging system's susceptibility to reflections and lighting conditions at certain angles has occasionally limited image quality. This has caused analysis difficulties, particularly during the detection of fine and small-sized defects such as pitting.

When evaluating the impact of the findings on industrial applications, it is observed that the proposed system could contribute to rapid data set production and the training of quality

control systems as a low-cost prototype. In the future, it is planned to enhance the system with deep learning-based algorithms for real-time marking of defective areas and automatic classification of defect types. Additionally, increasing adaptability to different material types and production processes will strengthen the system's flexibility and effectiveness in industrial applications.

5. Conclusions

In this study, a prototype system that can be integrated into a deep learning-based imaging system has been developed to collect real-time data on surface defects that occur in aluminum production processes. The real-time data acquisition performance was demonstrated in the tests to be able to meet the production speed by operating at an average speed of 37 frames per minute (FPS). The system successfully captured aluminum surface images on a 1500 mm long moving conveyor line, with no loss of synchronization due to camera-sensor compatibility. Throughout the integration process on the production line, the system functioned seamlessly, without any problems.

The main objective of this study is not to develop a surface defect detection system but to design and produce a prototype conveyor belt and imaging system that can serve similar purposes. In this study, a new data set called the Aluminum Conductor Data Set (ACD) has been created using this system. The ACD dataset is one of the few datasets available in the literature, specifically focusing on surface defects in aluminum conductors. The ACD dataset comprises 1,624 images, including 423 instances of pitting, 400 instances of embossing, and 801 instances of scalping. The images were obtained through the prototype system that simulates industrial conditions and carefully labeled by field experts. Due to the limited number of datasets of this quality in the literature, the ACD dataset is expected to make significant contributions to future studies in the training and testing processes of new deep learning-based methods to be developed for both the detection and classification of surface defects.

The instantaneous capturing of the collected data and its transfer to the operator via the system interface is an important step towards the digitalization of quality control processes. This structure enables both the development of data-driven decision support systems and the analysis of recurring problems encountered in the production process. In the long run, the data obtained through this system will contribute to production optimization, reducing waste rates and improving overall product quality.

However, the system also has some limitations. In particular, the thermal stability of the processor and graphics processor under long-term operating conditions has not yet been extensively tested. In addition, the data labeling process is manual, so there are time and labor constraints in creating larger datasets.

Future research may focus on expanding the capabilities of the developed system to gather more comprehensive data on various material types and surface structures. With this data, it will be possible to automatically detect and classify surface defects using deep learning models that are trained on the collected information. Additionally, studies may explore the integration of optimized processors and active cooling solutions to enhance system performance at the hardware level. Testing the long-term stability and reliability of the system in continuously operating production lines is another crucial area of research. Furthermore, the integration of automatic labeling systems could be pursued to accelerate data processing and improve overall system efficiency.

In conclusion, this study is an important step in the design and prototyping of a real-time and integrated data acquisition system that can be used in aluminum production. The developed system provides a powerful platform that is a preliminary preparation for deep learning-based quality control applications in the field. With future improvements, it is possible to transform this system into a highly efficient structure that will enable autonomous defect detection in industrial applications.

Ethics committee approval and conflict of interest statement

This article does not require ethics committee approval. This article has no conflicts of interest with any individual or institution.

Acknowledgment

This study was supported by Erciyes University BAP unit within the scope of University-Public/Private Sector/Industry Collaborative R&D Project (UKSP) with the code FÜKS-2024-13644 and our study was carried out in Hasçelik Kablo San. Tic. A. Ş. R&D Center. We would like to thank the company and Erü BAP unit for their contributions.

References

[1] Chen Y, Ding Y, Zhao F, Zhang E, Wu Z, Shao L. Surface defect detection methods for industrial products: A review. Applied Sciences 2021;11:7657.

[2] Tercan H, Meisen T. Machine learning and deep learning based predictive quality in manufacturing: a systematic review. Journal of Intelligent Manufacturing 2022;33:1879-905.

[3] Wen X, Shan J, He Y, Song K. Steel surface defect recognition: A survey. Coatings 2022;13:17.

[4] Liu X, Miao X, Jiang H, Chen J, Chen Z. Fault diagnosis in power line inspection using normalized multihierarchy embedding matching. IEEE Transactions on Instrumentation and Measurement 2023;72:1-10.

[5] Senavirathna SK, Udawatte H, Harischandra N, Fernando M, Ekanayake C. Image-based condition monitoring of transmission line conductors using image processing and deep neural networks. In: 2023 IEEE 17th International Conference on Industrial and Information Systems (ICIIS). 2023, p. 388-93.

[6] Zhang Y, Li B, Shang J, Huang X, Zhai P, Geng C. DSA-Net: An Attention-Guided Network for Real-Time Defect Detection of Transmission Line Dampers Applied to UAV Inspections. IEEE Transactions on Instrumentation and Measurement 2023.

[7] Wei X, Yang Z, Liu Y, Wei D, Jia L, Li Y. Railway track fastener defect detection based on image processing and deep learning techniques: A comparative study. Engineering Applications of Artificial Intelligence 2019;80:66-81.

[8] García DF, Usamentiaga R. Rail surface inspection system using differential topographic images. IEEE Transactions on Industry Applications 2021;57:2994-3003.

[9] Ge J, Xie S, Wang Y, Liu J, Zhang H, Zhou B, et al. A system for automated detection of ampoule injection impurities. IEEE Transactions on Automation Science and Engineering 2015;14:1119-28.

[10] Sun J, Li C, Wu XJ, Palade V, Fang W. An effective method of weld defect detection and classification based on machine vision. IEEE Transactions on Industrial Informatics 2019;15:6322-33.

[11] Zhou X, Wang Y, Zhu Q, Mao J, Xiao C, Lu X, et al. A surface defect detection framework for glass bottle bottom using visual attention model and wavelet transform. IEEE Transactions on Industrial Informatics 2019;16:2189-201.

[12] Zhang Y, Huang X, Jia J, Liu X. A recognition technology of transmission lines conductor break and surface damage based on aerial image. IEEE Access 2019;7:59022-36.

[13] Liu Y, Wang J, Yu H, Li J, Li F, Zhao Q. A non-invasive system for on-line surface defect detection on special-shaped steel towards real production lines. In: 2022 IEEE International Instrumentation and Measurement Technology Conference (I2MTC). 2022, p. 1-6.

[14] Ma Z, Li Y, Huang M, Huang Q, Cheng J, Tang S. Automated real-time detection of surface defects in manufacturing processes of aluminum alloy strip using a lightweight network architecture. Journal of Intelligent Manufacturing 2023;34:2431-47.

[15] Bükücü ÇC, Gökrem L. A new prototype that performs real- time error detection in glass products. International Journal of Engineering Research and Development 2020;12:510-9.

[16] Akbaş T, Özarslan C, Hacıyusufoğlu AF. Prototip bir marul tohumu temizleme ve sınıflandırma makinasının tasarımı ve imalatı. Anadolu Tarım Bilimleri Dergisi 2020;35:157-66.
[17] Zhuxi M, Li Y, Huang M, Huang Q, Cheng J, Tang S. A lightweight detector based on attention mechanism for aluminum strip surface defect detection. Computers in Industry 2022;136:103585.
[18] Wang M, Yang L, Zhao Z, Guo Y. Intelligent prediction of wear location and mechanism using image identification based on improved Faster R-CNN model. Tribology International 2022;169:107466.
[19] Nguyen HT, Yu G, Shin N, Kwon G, Kwak W, Kim J. Defective Product Classification System for Smart Factory Based on Deep Learning. Electronics 2021;10:826.
[20] Lv S, Ouyang B, Deng Z, Liang T, Jiang S, Zhang K, et al. A dataset for deep learning based detection of printed circuit board surface defect. Scientific Data 2024;11:811.
[21] Guclu E, Aydin I, Akin E, Akın E. Enhanced defect detection on steel surfaces using integrated residual refinement module with synthetic data augmentation. Measurement 2025;250:117136.
[22] Kim B, Shin M, Hwang S. Design and Development of a Precision Defect Detection System Based on a Line Scan Camera Using Deep Learning. Applied Sciences 2024;14:12054.
[23] Ren J, Zhang H, Yue M. YOLOv8-WD: Deep Learning-Based Detection of Defects in Automotive Brake Joint Laser Welds. Applied Sciences 2025;15:1184.
[24] Pallavi D, Miller S, Gunay E, Jackman J, Kremer GE, Kremer PA. Deep learning-powered visual inspection for metal surfaces– Impact of annotations on algorithms based on defect characteristics. Advanced Engineering Informatics 2024;62:102727.
[25] Vijayakumar A, Vairavasundaram S. Yolo-based object detection models: A review and its applications. Multimedia Tools and Applications 2024:1-40.
[26] Russell BC, Torralba A, Murphy KP, Freeman WT. LabelMe: a database and web-based tool for image annotation. International Journal of Computer Vision 2008;77:157-73.